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Locating real-time water level sensors in coastal communities to assess flood risk by optimizing across multiple objectives

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Coastal communities around the world are experiencing increased flooding. Water level sensors provide real-time information on water levels and detections of flood risk. Previous sensor installations, however, have relied on qualitative judgments or limited quantitative factors to decide on sensor locations. Here, we provide a method to optimally place real-time water level sensors across a community. We utilize a multi-objective optimization approach, including traditional measures of sensor network performance such as coverage and uncertainty, and new flood-specific parameters such as hazard estimations (flood likelihood, critical infrastructure exposure), serviceability (sensor accessibility), and social vulnerability (socio-economic index, vulnerable residential communities index). We propose a workflow combining quantitative analyses with local expertise and experience. We show the method is able to reduce the set of possible new sensor locations to just 1.3% of the full solution set, supporting effective and feasible community decision-making. The method also supports sequential expansion of a sensor network, creating a network that provides detailed and accurate real-time water level information at the hyperlocal level for flood risk assessment and mitigation in coastal communities.

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Climate change is leading to rising sea levels and increasing frequency and severity of storm events. Combined with varying environmental and social factors, this is leading to increasing flood risk for coastal communities around the world[1–4]. At the same time, real-time sensor technologies are both improving in capability and decreasing in cost to install and maintain[5,6]. The recent growth of water level sensors, in particular, provides communities with real-time information on water levels across the waterways intersecting a coastal community and detections of flood risk[7–11]. Compared to existing water level monitors, e.g., a single tide gage offshore, creating a network of water level sensors distributed across an area provides much more detailed and accurate information about water levels in a coastal community than was previously possible to obtain[12].

This study looks at placing water level sensors in a coastal community to provide hyperlocal and real-time information for both flood risk mitigation (providing information on how water levels change over different areas of a coastal community over time) and emergency flood response (indicating the real-time impacts of a given flood event in a community). To maximize the benefit of such a water level sensor network requires that sensors be located strategically across a community. While it is desired to monitor and provide information about as much of an area as possible, in reality, resources are limited, and a limited number of sensors can be installed to provide flood risk assessment in the coastal community. This study provides a method to optimally locate real-time water level sensors across a community considering multiple objectives—including objectives not traditionally included in such decision-making processes—to assess flood risk.

Traditional quantitative sensor placement methods consider two main objectives in placing and expanding a network of sensors: increasing coverage of the network, i.e., increasing the area that is covered and monitored by the sensors; and decreasing uncertainty in the network assessment, i.e., decreasing the uncertainty in the information about the whole area based on the limited information from the sensors[13,14]. Though there have been some optimization methodologies that combine network utility parameters[15], there is no study that combines flood risk, social vulnerability, and infrastructure exposure in the assessment of sensor networks. For water sensor networks, previous methodologies focus on a single parameter, which is to minimize the uncertainty in regions with no sensors[16]. This technique, however, assumes that all regions are treated equally and there is no inclusion of social vulnerability. In contrast, many coastal regions are diverse, with diverse communities composed of varying populations, housing characteristics, critical infrastructure distributions, and varying levels of flood risk. Alternative qualitative sensor placement approaches are based on the experience and expertise of members of the local community, including planning personnel and emergency managers, who have had experience with multiple flood events over many years. Both quantitative and qualitative approaches present key limitations. Existing quantitative approaches fail to account for additional measures relevant to flood risk, particularly critical infrastructure exposure[17,18] and social vulnerability measures that are critical to protecting vulnerable coastal populations and increasing resilience to the impacts of climate change[19–22]. Existing qualitative approaches fail to provide a quantitative basis or rationale for sensor installations[23]. Installation decisions may be subject to historical biases and overlook certain areas of a community that are critical areas that would benefit from real-time flood monitoring.

To address this gap, we propose a method for optimizing the placement of real-time water level sensors across a coastal community that considers multiple objectives, including sensor-related (sensor coverage and network uncertainty), flood-specific (flood hazard and proximity to critical facilities), and social (socioeconomic and community vulnerability) parameters. The sensors are treated as a network, which together provide real-time information about water levels across a community. In the method, we include traditional measures of sensor network performance such as coverage and uncertainty, as well as new coastal flood-specific parameters such as hazard estimations (flood likelihood, critical infrastructure exposure), serviceability (sensor accessibility), and social vulnerability (socio-economic index, vulnerable housing, and residential communities index). In addition, we propose a workflow for decision-making in sensor placement that maintains local expertise and experienced intuition as key components of the process. This study is the first of its kind to systematically consider multiple objectives in the installation and expansion of a water level sensor network for flood risk assessment in coastal communities.

The method utilizes a multi-objective optimization approach combined with geographic information system visualization to facilitate both quantitative analyses of sensor placements considering multiple factors and communication with community decision-makers. We illustrate the approach with a network of water level sensors that has been installed and is currently in operation along the coast of the state of Georgia, USA. The project represents a partnership between academic researchers and Chatham County, GA, officials to utilize new cutting-edge sensor technologies to assess and mitigate flood risk for coastal populations across the county.

What follows is first the description of the range of sensor network parameters included in the methodology. Applying the proposed approach to the Chatham County, GA, area and network of sensors, we then describe the full solution space of possible sensor locations and how to obtain the solution locations for new sensor placements. Results show that the method provides effective decision support by narrowing the number of possible sensor installation locations across a large area to a much smaller feasible set of solutions based on the range of parameters of interest. Given the long-term monitoring goals of these sensor network projects, we then demonstrate how the method supports the sequential expansion of the network as resources become available for additional sensor installations. Comparing results from our proposed method with those from traditional approaches shows the importance of considering multiple objectives in the sensor placement decisions to assess flood risk in a community. We find that it is critical to include a full suite of sensor-related, flood-specific, and social objectives in the analysis if we are to leverage new sensor technologies to provide comprehensive and accurate assessments of flood risk across coastal communities. The results provide a roadmap and methodology for other coastal communities to utilize and implement as they install sensors that provide real-time water level information for flood risk mitigation and flood impact assessment in their communities.

Results

Range of sensor network parameters. To find strategic and optimal new sensor installation locations, we include five main network parameters covering sensor-related, flood-specific, and social measures: network coverage, network uncertainty, critical infrastructure facilities density, flood zone, and damage assessment priority index. We perform a quantitative analysis for each of these network parameters for each potential new sensor location by calculating each parameter value for the current network of sensors plus the inclusion of the new potential sensor location. Potential new sensor locations are defined by a grid over the study area, with each new location modeled as a square defined by the grid size and the latitude and longitude value at its center. This definition allows the method to be flexible to having locations and corresponding grid cell sizes with variable dimensions based on the region of analysis and its geography or other characteristics. The total number of possible locations is then determined by the cell size and extent of analysis, both of which can be modified as needed by community decision-makers.

At each feasible new sensor location, we calculate the five network parameters. The methodology presented considers adding sensors to the network one at a time, rather than the simultaneous placement of multiple sensors at the same time. The application of the method to the sequential expansion of the network with the placement of multiple new sensors over time is considered later in this paper. The following describes each network parameter in detail and provides the corresponding plot of the parameter values across the study area. See the "Methods" section for further details on the specific calculations for each parameter.

The network coverage parameter quantifies the increase in coverage provided by a new sensor location. Network coverage is measured by the total count of additional feasible locations for which inundation can be mapped within a 20% error threshold with the addition of a sensor at a given location. Inundation is mapped by using an objective mapping algorithm that determines the inundated areas over a region using a Gaussian error function with a decay distance of 5 km from a given sensor. The decay distance indicates the distance over which a sensor's water level reading can effectively be interpolated, determines where the 20% error threshold occurs (i.e., how far from a given sensor), and can be adjusted as desired by a modeler. For network coverage, the goal is to maximize the increase in network coverage (i.e., maximize the number of additional locations mapped) with the placement of a new sensor (Fig. 1a).

In Fig. 1, the entire area of analysis is shown, with parameter values at each location colored from light to dark blue based on the given scale. The grid cell size is 100 m by 100 m. Waterways are shown in underlying grey. In Fig. 1a for network coverage, the number of added locations covered with the addition of a new sensor at a given new sensor location—measuring increased network coverage—is shown. The darker blue indicates more new locations are added; the lightest blue indicates that no new locations are added. Because the existing sensors, shown as triangles, already provide coverage over some of the areas, the locations closest to the existing sensors have the lowest increase in network coverage and are therefore the lightest color. The darkest blue areas indicate the locations where it is most effective to locate a new sensor to increase the network coverage.

Network uncertainty is measured by the mean error value across the inundation map with the addition of information from each new possible sensor location solution. This error value is calculated simultaneously with the network coverage parameter when building the inundation map using a Gaussian error function and a decay distance of 5 km from a given sensor. It represents the confidence level associated with the interpolated water level at each point in the solution space, i.e., based on proximity to the water level sensors in the network, with a higher percent error indicating lower confidence. The objective is to minimize the uncertainty or maximize the decrease in error, from placing a new sensor in the network (Fig. 1b). In the figure, the darkest blue represents the lowest mean percent error over all locations, indicating it is most effective to place a sensor in these locations to decrease network uncertainty.

In the assessment of critical infrastructure facilities density, we include hospitals, police stations, power facilities, and schools. These facilities were chosen based on priorities indicated by the Chatham Emergency Management Agency (CEMA). Additional facilities can be included in the methodology based on specific community preferences using the same analysis approach. We use a kernel density measure to capture the new sensor proximity to critical infrastructure to maximize the ability of new sensors to measure critical infrastructure flood exposure (Fig. 1c). The critical facilities are shown in yellow circles. The kernel density is measured as the number of facilities per square distance. Using a kernel rather than a point density metric results in a more continuous outcome for this critical infrastructure facilities density parameter. In the calculation of kernel density, a continuous surface is created around each facility, with its value equal to 1 at the location of the facility and a quartic decay with distance away from the facility to a value of 0 at a specified radius from the facility. Figure 1c shows the resulting kernel density, measured as the number of facilities per square kilometer, computed using a radius of 1 km. The selected radius can also be varied based on factors such as the level of urbanization of a region or the population density served by the critical infrastructure. In Fig. 1c, the darkest blue indicates locations with the highest critical infrastructure facilities density values.

As the purpose of installing water level sensors is to provide real-time flood information across the community, flood zone information is also critical to include. FEMA flood zones are used as a proxy for the likelihood of flooding in each area across the county, with the goal of providing more detailed water level monitoring at higher likelihood flood locations (Fig. 1d). The defined flood zones for Chatham County are as follows. Flood zone VE and all A zones indicate areas subject to the 100-year flood, i.e., they will be inundated by the flood event having a 1% chance of being equaled or exceeded in any given year. Flood zone VE is denoted as the highest risk area because, in addition to being subject to the 100-year flood, it is located in a coastal area with additional coastal hazard exposure including exposure to storm-induced waves >3 feet. Subgroups of zone A include zones AE, AH, and A99. Compared to zone A, zone AE includes additional base flood elevation (BFE) information indicating the elevation for which floodwater is anticipated to rise during the 100-year flood, obtained from performing detailed hydraulic analyses of the area. Thus, with the lack of information, zone A—where detailed hydraulic analyses have not been performed and BFE information is not available—is categorized as the next highest risk area, followed by zone AE. Zone AH is subject to shallow flooding of 1–3 feet with anticipated impacts that are less severe, and zone A99 indicates areas that will be protected by a Federal flood protection system. Therefore, these two zones comprise the next highest risk category. Next, zone X_500 has a moderate flood risk, indicating areas that lie between the limits of the 100-year and 500-year flood events. Zone X are low flood hazard areas and lie outside the 500-year floodplain. All zones are shown in Fig. 1d. Open water, where a FEMA flood zone designation is not applicable, is indicated with hatched lines. In the figure, the darkest blue indicates locations with the highest flood risk.

Finally, social vulnerability is included through an index developed by CEMA called the Damage Assessment Priority Index (DAPI). This metric combines multiple socioeconomic and social vulnerability indicators and is currently used during CEMA's disaster (e.g., floods, hurricanes) response process to prioritize damage assessment activities. Specifically, it includes socioeconomic indicators (households below the poverty level, homes that receive SNAP assistance, unemployed population), vulnerable residential indicators (number of households that are renter-occupied and owned with no mortgage), and vulnerable housing unit indicators (type of housing unit, number of mobile homes, small/medium/large multi-unit homes). Locations are ranked based on these three sets of indicators from most

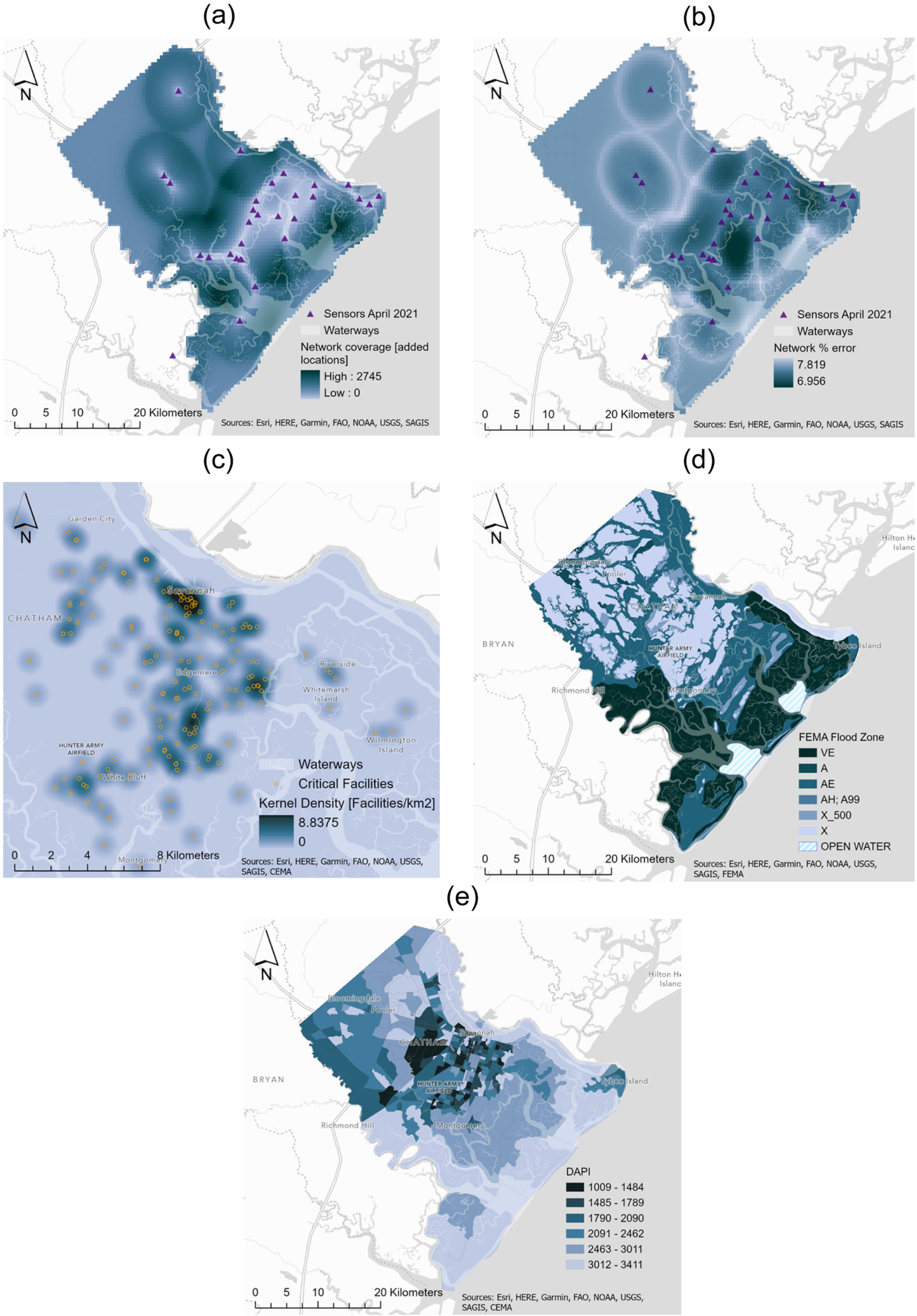

Fig. 1 Sensor network parameters. a Network coverage is measured by the number of added locations covered by placing the sensor in the new location. **b** Network uncertainty measured by the mean error in the inundation map. **c** Critical infrastructure facilities density as measured using a kernel density. **d** FEMA flood zones indicating the likelihood of flooding. **e** Damage Assessment Priority Index (DAPI) ranking social vulnerability.

vulnerable (lowest ranking number) to least vulnerable (highest ranking number), and the DAPI is composed of the sum of these three rankings. The DAPI is used here in collaboration with CEMA to prioritize locations of new sensors near more vulnerable areas in the county (Fig. 1e). Final DAPI values range from 1009 to 3411. A lower DAPI ranking value indicates higher vulnerability and higher priority for locating new sensors, shown as the darkest blue locations in the figure.

As of April 2021, 30 sensors had been installed in Chatham County using largely qualitative approaches. The methodology proposed in this study was applied to provide decision support in identifying the locations for the next round of sensor installations in the county. Each sensor network parameter, as applied to the county and each potential new sensor location solution, is taken into account in the methodology (Fig. 1, see the "Methods" section for more detailed descriptions of the calculations of each parameter).

Assessing the full solution space of possible sensor locations. With the sensor network parameter values, we use these as inputs to identify optimal locations for the new sensor installations. Each parameter value is viewed as an objective in the optimization, leading to the formulation of a multi-objective optimization problem. With the goal of providing decision support in placing new sensors while maintaining local expertise and experienced intuition in deciding on new locations for the sensors, the purpose of the optimization is not to find a single best new location, but a small collection of feasible solutions so that the decision-makers are able to have clear quantitative analysis-based information from which to determine the final locations.

The full solution space for new sensor locations is defined by an extent, or bounding region, within which the sensor network parameter values are computed for all locations. We then map the waterways within this bounded region to show which of all the locations are feasible solutions for the installation of the flood level sensors for water level monitoring, which may consist of rivers, lakes, wetlands, open ocean waters, and other potential locations. Chatham County is bounded by the Ogeechee River, Savannah River, and the Atlantic Ocean. As the sensors measure water levels, this system of waterways within the county is the initial solution space for analysis. To facilitate ease of access for maintenance, ocean-facing locations and marshlands within the waterways are excluded from the solution space. The major waterways and their network of tributaries used as the solution space define the final extent of the analysis and cover the full set of feasible solution locations (Fig. 2a).

Next, the resolution of the analysis must be determined. Although it is most ideal to be able to conduct the analysis at a fine resolution, computational time and power need to be considered when determining a final resolution. Based on the resolution of layers utilized to compute each sensor network parameter, and in collaborative discussions with County officials, a final resolution of 100 m was selected for the Chatham County case. We have found this resolution to ensure sufficient detail in the level of analysis while maintaining computational efficiency. In general, collaborating with decision-makers about the final extent of the geographical area covered in the solution space and the desired and feasible resolution is essential. In addition, both area and resolution parameters can be adjusted over time as different goals are prioritized by decision-makers.

Obtaining the solution locations. Once the full solution space and appropriate resolution have been defined, we calculate the sensor network parameters for each feasible solution throughout the solution space (Fig. 2b–f). Metrics are quantitatively calculated and indexed by a coordinate pair (latitude, longitude) at the center of each grid cell, defined by the resolution, in the solution space. To compare metrics across feasible solutions and prioritize potential new sensor locations based on the calculated parameter values, we create an array for each possible solution that consists of the coordinate pair and five independent values, each corresponding to a different sensor network parameter. In Fig. 2, for each parameter, the darkest colors indicate prioritized locations based on the value of that parameter.

With these location-specific parameter values, the goal of the optimization process is to prioritize a subset of these solution locations that provide improved performance for the network across multiple objectives. Each sensor network parameter is viewed as a performance objective; hence, a multi-objective optimization problem is formulated. Using a multi-objective optimization algorithm, we find the resulting set of non-dominated solutions, where a non-dominated solution is one where none of the objective functions can be improved without degrading some of the other objective values. We achieve this by implementing a multi-objective optimization algorithm to find the Pareto frontier of the full solution space. The result is the prioritized set of solution locations, also known as the Pareto set, that is optimized across the multiple sensor network parameter values (see the "Methods" for more detailed description of the multi-objective optimization problem formulation). The prioritized Pareto set of non-dominated solutions is communicated to the community decision-makers for the final selection of new locations for sensor placement.

For the resolution and extent of analysis for the full solution space for Chatham County, the result is a total of 28,890 possible solution locations across the county, represented by coordinate pairs located at the center of each grid cell throughout the solution space. Having such a large number—almost 30,000—of potential locations for new sensor installations is impractical for decision-makers to effectively select from. Thus, the objective of the proposed methodology is to find a smaller optimal set from this group of locations to support more effective community decision-making. For the Chatham County case, implementing the multi-objective optimization algorithm over the full solution set reduces the original set of 28,890 possible sensor locations to a set of 381 non-dominated solutions. This result represents just over one percent of the original set (1.3%). The reduction from the full solution set to the prioritized set of locations indicates the ability of the methodology to select a much smaller subset of solutions from the original full solution space. The results provide decision-makers with a reduced set of solutions from which an effective and feasible decision can be made.

To further facilitate communication of the prioritized set of new sensor locations with community decision-makers, the set of non-dominated solutions, along with the computed metrics for each solution, are plotted geographically with the coordinates of each solution (Fig. 3). For the Chatham County case, most of the found potential locations for new sensors are not near the current sensors, indicating that the selected locations help the network to grow in coverage. From the methodology, the selected locations also consider and optimize new locations based on the other uncertainty, flood hazard, and social vulnerability metrics. Moreover, from the solution locations found, most potential locations are clustered, so decision-makers do not need to choose from 381 locations but instead from dozens of clusters. These solution clusters are highlighted in Fig. 3. Since the overall methodology is meant to be a decision support tool, utilizing an interactive geographic information system-based interface to visualize and communicate the prioritized solution set allows users to weigh the benefits and drawbacks of potential new sensor locations. Decision-makers can identify clustered regions of non-dominated solutions, understand the value of certain locations through the visualized metrics, and use their geographic expertise and intuition from experience to select a specific location within a clustered region to support a sensor installation.

Supporting sequential expansion of the network with new sensors over time. One of the keys in the methodology is that the process of expanding a network of sensors is a continuous one. As

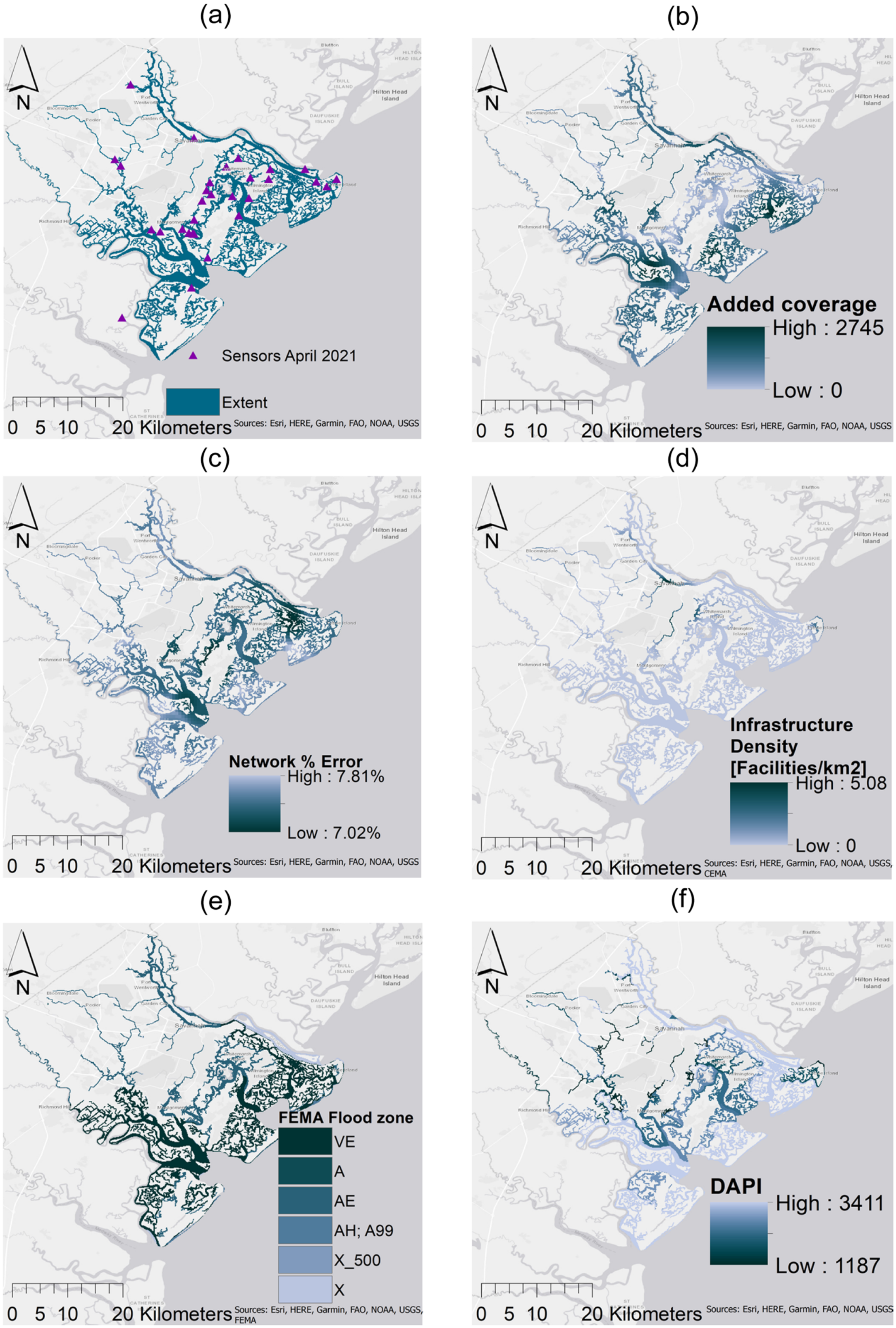

Fig. 2 Sensor network parameters calculated for all possible solution locations. a Extent of the solution space covering a full set of feasible solutions. **b** Network coverage over the extent. **c** Network uncertainty over the extent. **d** Critical infrastructure facilities density as measured using a kernel density. **e** Flood zone over the extent. **f** Social vulnerability ranking as measured by the Damage Assessment Priority Index (DAPI).

more funds become available and sensor technologies become less expensive and more widely available, more sensors can be installed over time. The decision of locations to install new sensors is not a one-time decision. Instead, as we have found in the work with Chatham County, it is desired to be able to continually and optimally expand the sensor network over time. The methodology proposed in this study supports a sequential expansion of the network with new sensors over time. To do this, the

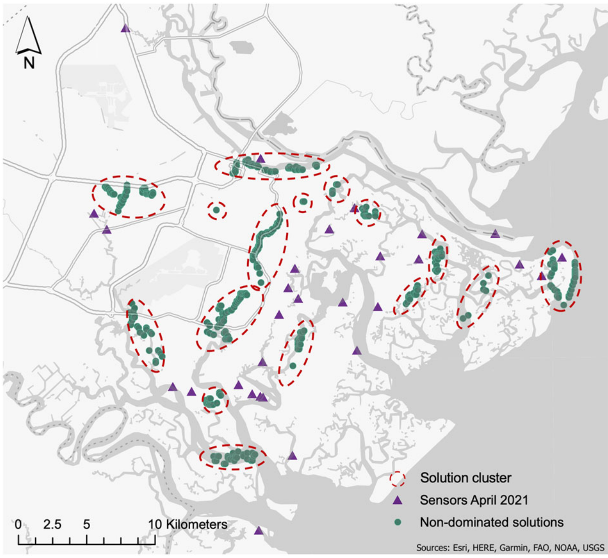

Fig. 3 Set of non-dominated solutions resulting from the multi-objective optimization process. Non-dominated solutions give a prioritized set of new sensor locations, and clusters of solutions among the full non-dominated solution set are highlighted.

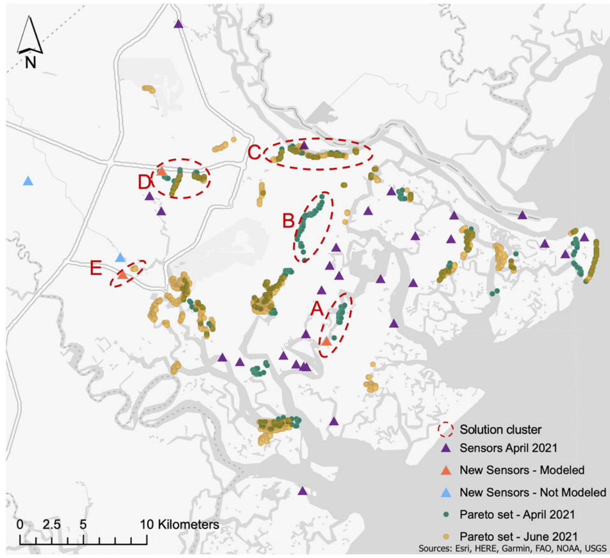

Fig. 4 Sequential expansion sensor network showing locations of new sensor installations and evolution of non-dominated solutions after including a new set of sensors. Existing sensor locations (purple triangles), prioritized Pareto set of potential new sensor locations found from running proposed multi-objective optimization model (green circles), five main solution clusters identified and considered in collaboration with community decision-makers (dashed red ellipses A–E), selected new sensor locations based on decision-making process (orange and blue triangles), and new set of prioritized non-dominated solution locations with an updated network of sensors (gold circles).

methodology is run to find optimal new sensor locations. These found sensor locations are then tested by going through the methodology again and including the coordinates of the new sensor locations when computing the varying sensor network parameters. This then provides updated results considering how the new sensor locations affect the next set of non-dominated solutions.

What follows is a description of how we combined the obtained solution location results from the proposed multi-objective optimization methodology with local expertise from community decision-makers to place new sensors in the water level sensor network in Chatham County (Fig. 4). Beginning with the sensors in the existing April 2021 network (purple triangles), we ran the proposed multi-objective optimization model, resulting in the prioritized Pareto set of potential new sensor locations (green circles). From the research team's collaboration with Chatham County officials, five main clusters of resulting non-dominated solutions were identified and considered for new sensor placement. The described process provides examples of the real-world considerations that come into play in actual sensor placement decisions and insights into how the proposed methodology has been and can be implemented in practice.

Considering cluster A of potential solution locations, we see that is located in the middle of an area of several existing sensor installations. Community decision-makers noted they had stopped considering this area for new sensors due to the number of sensors already in the area. However, on closer analysis of the model results, they realized there are no sensors specifically targeting this tributary river. Using satellite imagery, they found private boat docks that would be suitable for installing a sensor and easily accessible for future maintenance, contacted the owners of the docks, and came to a decision on where exactly to install the new sensor (orange triangle).

Another cluster of solutions investigated was seen by cluster B on the map. However, this tributary river was recognized as being controlled and monitored by Chatham Engineering using flood-gates and was therefore removed from the extent for future analysis. The solution locations in cluster C were found to effectively address multiple objectives, including network coverage, critical infrastructure, and vulnerable communities. However, this major river is populated by corporate shipping docks. Through the model results and visualization of network parameter values at this location, city officials see the benefit of locating a new sensor in this area. Thus, they have been working to obtain access permits for a new sensor installation at this location. It is noted that the existing sensor near that cluster is installed on one of the few city-owned plots in the area.

Cluster D shows a cluster of solutions that would improve both network coverage and uncertainty around a few sensors already located inland, so a location for a new sensor installation was selected in that area based on the model results. One of the main objectives in this round of sensor installations was to gradually move the network inland. Therefore, a sensor was installed at cluster E based on the model results. Beyond cluster E, as there are fewer communities and less infrastructure inland, the most inland location was not explicitly selected by the optimization model. However, because monitoring rivers upstream can help predict how inland rainfall may affect flooding at the coast, a sensor was installed (blue triangle). Throughout this process, involving local expertise in deciding the final location of new sensors ensures that the intuition of community experts still plays a key role in the network expansion.

After installing these new sensors, the model was run again with the updated network of sensors, to obtain a new set of prioritized non-dominated solution locations based on the June 2021 network (gold circles). New regions of interest can be seen, with new clusters of solutions surfacing throughout the County as potential new strategic sensor installation locations. The updated Pareto set no longer includes locations by cluster A, indicating that the recently installed sensor improved the network parameters in that area. Solutions are not seen by cluster B since that tributary river was excluded from the extent. Solution locations continue to be identified at cluster C, indicating the priority to find a suitable sensor installation location in that area. Additional clusters of solutions appear, which can be weighed

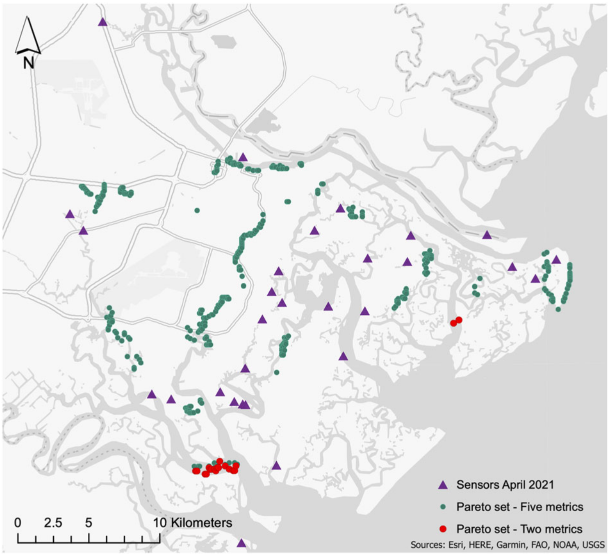

Fig. 5 Comparison between identified prioritized potential new sensor locations using traditional two metrics of coverage and uncertainty and using new metrics covering sensor-related, flood-specific, and social parameters as proposed in this study. Existing sensor locations (purple triangles); prioritized Pareto set of potential new sensor locations based on only two metrics of coverage and uncertainty (red circles); and prioritized Pareto set of potential new sensor locations based on the full set of five metrics as proposed in this study including network coverage, network uncertainty, critical infrastructure facilities density, flood likelihood, and Damage Assessment Priority Index (DAPI) ranking social vulnerability (green circles).

with community goals in future sensor placement decisions, such as the goal of continuing to expand the network inland or to prioritize certain areas for monitoring. The results show how the sensor network expansion process can be sequentially approached with every new sensor installation and continuously adjusted to maintain alignment with community goals. Different scenarios of new sensor installations can be tested and compared using this process. Based on a community's priorities, decision-makers can consider selecting different sensor locations to improve certain metrics and achieve selected community goals over time.

Comparison with traditional sensor network expansion approaches. The prioritized new sensor locations found are based on the full suite of proposed sensor network parameters, including sensor-related, flood-specific, and social measures. The resulting locations are significantly different than those found using just the traditional sensor network expansion parameters of network coverage and uncertainty (Fig. 5). From the conventional two-metric solution, new locations are optimized by filling gaps in the network coverage, remaining nearby to existing sensor locations to decrease the uncertainty of the inundation profile but just far enough from the dense region of sensors to gradually increase the coverage of the inundation profile. In comparison, using the full set of parameters as proposed in this study results in a solution set that still includes some of the previous solutions, but also provides clusters of solutions in other regions of the county that account for other sensor network objectives.

Discussion

The installation and use of water level sensors to provide real-time flood information in coastal communities are becoming more widespread. Most previous installations of these sensors have been ad-hoc, however, relying on qualitative judgments to decide on sensor locations. This approach leaves the process open to biases and the potential to neglect critical areas of a community. The few existing studies on using quantitative measures to support decisions for sensor placement and network expansion rely on the limited set of parameters of network coverage and uncertainty, neglecting such critical factors as flood risk, social vulnerability, and critical infrastructure exposure.

The results from this study show the importance of simultaneously considering a range of factors when deciding on the placement locations for new sensors for a network of water level sensors. In this work, we describe five parameters in particular that cover a wide range of variables of interest to flood-prone coastal communities. These include network coverage indicating how much of an area for which information on water levels is able to be obtained based on the sensor information, network uncertainty indicating the accuracy of that information, critical infrastructure facilities density indicating the proximity of a sensor to provide data on flood exposure of critical assets, flood zone indicating flood risk of a particular area, and damage assessment priority index indicating social vulnerability of a location.

By including all of these parameters in the decision-making process, the sensors provide information on the wide-ranging impacts of flood events. In particular, the data considers the geographical spread of flood events (network coverage), the complexities and potential errors in assessing and predicting flooding (network uncertainty), the importance of protecting critical assets in a community during storms (critical infrastructure facilities density), the underlying hazard level of an area (flood zone), and the social vulnerability of the populations impacted by flood events (damage assessment priority index).

Each of these factors is important for both flood risk mitigation activities and providing real-time water level information for emergency flood response. Increasing network coverage with new sensors means a wider area is able to be monitored during flood events and a larger area is assessed for flood impacts. Decreasing network uncertainty increases the confidence of community leaders in the collected sensor data on which to base hazard mitigation and emergency response decisions. Increasing monitoring near critical infrastructure facilities provides real-time information on the flood status at these critical facilities that affect human health and safety (hospitals and police stations), provide critical services that impact the ability of large portions of the population to survive and continue to function through storm events (power facilities), and provide space and resources for flood response activities (schools). For risk mitigation, prioritizing new sensor locations near critical infrastructure also provides the hyperlocal information needed to make site-specific mitigation decisions to protect individual facilities. Prioritizing data collection in high flood-risk areas based on flood zone provides information at locations more likely to experience flood events and severe flood impacts from storms. Increasing data collection in areas with higher social vulnerability increases the amount of information available to use in risk mitigation and emergency response decisions to decrease the risk for more vulnerable populations.

In applying the approach to other coastal communities, the sensor network parameters can be directly applied, or adjusted and tailored to the specific needs and data availability of the particular location and study area. Network coverage and network uncertainty can be directly applied to any study area, with variations in the geographical boundaries of the extent of analysis as desired by community decision-makers. The resolution and grid cell size for calculation of the parameter values can be similarly varied, with additional considerations for parameter data availability and computational complexity. Critical infrastructure facilities density can be defined based on the accessible information and the priorities of a community in terms of the specific facilities to be included in the analysis. In addition to the hospitals, police stations, power facilities, and schools considered for Chatham County, critical infrastructure that would be of relevance to consider for coastal communities include bridges, fire stations, water treatment plants, and wastewater treatment facilities.

Flood zone assessments of risk are based on nationally available data and are applicable across the US. Other assessments of flood hazard risk would be applicable for other international communities, with the important information to include being the relative risk of locations across the community and indications of the hazard areas to prioritize in the methodology. While the particular calculation of the damage assessment priority index (DAPI) is specific to Chatham County, its concept is widely applicable to other locations. If the data used to calculate the DAPI is available in a particular location, the DAPI can be directly used. Otherwise, other social vulnerability measures can be included or replaced with those used in the DAPI according to the available data and community priorities. The goal of this parameter is to support flood risk assessment and mitigation activities for the most vulnerable populations in a community.

With this range of parameters of importance to consider, in this study, we present a new methodology that utilizes multi-objective optimization to rigorously and quantitatively account for all parameters in the placement decisions for new real-time water level sensors. Beginning with all possible locations for a new sensor placement across an area, we show that the approach is able to effectively reduce the full set of possible locations (28,890 locations in Chatham County, GA) into a much smaller optimal and feasible set of sensors locations (381 locations). This two-order-of-magnitude reduction in possible locations shows the method to provide effective decision support in locating new sensor placements.

Comparing the solution location results obtained based on the full set of five parameters with those from using only the traditional measures of increasing network coverage and decreasing network uncertainty shows a significant difference between the two solution sets. The results demonstrate the importance of including the full suite of sensor-related, flood-specific, and social measures in the analysis. While this study includes results from the combined five parameters (network coverage, network uncertainty, critical infrastructure facilities density, flood zone, and damage assessment priority index), in extending this work to other locations and communities, additional parameters can also be included in the analysis if such data is available and if it is so desired by community decision-makers. Fewer parameters may also be used if there is a lack of data on any of them. In either case, the difference is that the number of objectives in the multi-objective optimization problem would change to match the number of parameters. Overall, the key is that we encourage communities to expand the set of parameters considered in sensor placement decisions and to systematically and objectively assess these parameters in making the decision. We find that the set of five parameters achieves a good balance between basing the decision on a wide range of information of importance to flood risk assessment, while not considering too many parameters to clutter the data presentation to community decision-makers.

To facilitate communication of the results with community decision-makers, we integrate the solutions from the multi-objective optimization problem with a geographic information system visualization. This visualization interface supports communication and assists in placement decisions. Specifically, we find through the visualization that many of the solution location results are clustered. Considering each cluster individually enables decision-makers to utilize their experience and expertise to decide on final installation locations. In practice, the final locations were selected within individual clustered solutions. This process combining the multi-objective optimization with community leader input enables the sensor placement decisions to be made based on quantitative analyses combined with locale-specific factors that may not be captured in the direct assessment of the varying parameters across the study area of interest.

Considering the long-term monitoring goals for the installation and maintenance of a real-time water level sensor network in a coastal community, we also show how the method can be used to support the sequential expansion of the network. As resources become available and the size of the network grows over time, the method we present can be applied again and again to continually expand the network and ensure that the sensors collect data with increasing benefit at each step. A further unique aspect of this study is the ongoing collaboration between the research team and Chatham County officials. Throughout this study, we demonstrate how the methodology can be and has been used in a real-world sensor network deployment, moving the study from the lab to the community to support real decisions in sensor placement.

Our findings in this study provide a roadmap for other coastal communities to utilize and implement to create and expand networks of water level sensors in these communities. The method enables sensor placement decisions to be made based on quantitative analyses accounting for multiple objectives, including sensor-related, flood-specific, and social vulnerability measures. The resulting workflow for decision-making in strategic and optimal sensor placement accounts for the quantitative sensor network parameters while maintaining local expertise and experienced intuition as key components of the process. The result is a network of sensors that provides real-time water level information at the hyperlocal level for flood risk assessment and mitigation in coastal communities.

Methods

This section describes our multi-objective water level sensor placement method to provide real-time monitoring of flood levels in coastal communities in further detail. Let L denote the set of possible locations for new sensor placements. The set L is defined based on the extent, i.e., bounding region, of analysis; resolution, i.e., grid cell size, for analysis; waterways indicating feasible locations for water level sensor installations; and sensor network coordinates providing locations of any existing sensors in the network. The goal is to reduce this full set L into a solution location s. This is accomplished through computing parameter values at each possible location $l \in L$, conducting a multi-objective optimization over these parameters to obtain a prioritized set of non-dominated solutions $P \subseteq L$, before selecting the final sensor location $s \in P$. The multi-objective optimization includes five main sensor network parameters: network coverage, network uncertainty, critical infrastructure facilities density, flood zone, and damage assessment priority index. Each of these parameters is calculated as follows.

Network coverage. Network coverage of any feasible sensor location l is measured by computing an inundation mapping algorithm with the current network of sensors plus location l as a potential new sensor location. The inundation mapping algorithm uses an objective mapping algorithm to determine inundated areas over a region. It has been widely used in creating gridded maps of climate and oceanographic data fields using sparse instrumental observations as input[24–27]. In this case, the input are the measurements from the water level sensors. The implemented algorithm utilizes a decay distance of 5 km, conservatively optimized using a Gaussian correlation matrix of the sensor locations throughout the county, over which a sensor's water level reading can effectively be interpolated. The decay distance can also be adjusted as the number and density of sensors within the network increase over time. Based on this correlation matrix and the water level readings from all sensors at a given time, a water level layer is generated throughout the county for all feasible locations. A LiDAR Digital Elevation Model of the county is then subtracted from the water level layer to compute the inundation layer, which is a representation of water depth above the ground level throughout the county at a particular time. To reduce misleading inundation depths, a Gaussian error function is computed over the correlation matrix to quantify the error at every feasible location and point of the inundation map. This error value represents the confidence level associated with the interpolated water level at each point in the solution space, with higher percent error and lower confidence as the distance from a given sensor increases and in combination with information from nearby sensors if available. Locations are masked out if they have more than 20% error, the threshold used to provide conservative results for the purposes of emergency response and city planning. Note that the remaining error values are those used in the calculation of the network uncertainty parameter described following.

After removing grid cells throughout the inundation map with more than 20% error, the total count of remaining grid cells is used to calculate the network coverage. Specifically, to obtain the network coverage parameter value at a possible new sensor location l, the increase in the number of locations covered by the network with the new sensor location is calculated by subtracting the number of grid cells of the currently existing network of sensors (prior to including the new sensor at location l) from the total count of grid cells after including the new sensor at location l. The result gives the varying levels of increased value, as measured by an increase in network coverage, of a sensor placed at a given new location.

If a location l is within a high-density area of currently installed sensors, the network coverage may not be affected since that area was already included within the inundation mapping extent. That is, the surrounding locations were likely already included in the inundation map, and adding a new sensor in that location will not lead to a significant increase in the number of locations covered by the network. Adding a sensor at such a location will, however, likely improve the network uncertainty, as discussed below. If a location l is just outside the extent of a high-density area of currently installed sensors, the network coverage will likely be improved, as it provides information on water levels at a large set of new locations. If a location l is in an isolated area with no other nearby sensors, the network coverage may not be significantly affected since a single sensor may not provide high confidence inundation mapping, i.e., <20% error, for the region surrounding the isolated sensor. This holds true when adding sensors to the network one at a time. The outcome may change when considering the sequential expansion of the network with new sensors over time, as discussed in this paper. However, solving the problem for multiple sensors at the same time is not considered in this paper as it significantly increases the complexity and computational costs of the problem. At the same time, if a particular region has been identified by community decision-makers as a target for network expansion, the methodology presented in this paper can be adjusted to prioritize placing sensors in this new location.

Network uncertainty. Uncertainty at a possible new sensor location l is calculated simultaneously with coverage. Location l is included as a potential new sensor location when computing the inundation mapping algorithm, regions with greater than 20% error are removed as described in the calculation of the network coverage parameter, and then the mean error of all the remaining inundation grid cells is computed to calculate the network uncertainty parameter value associated with location l. Since water levels are likely to vary over short distances along a river, coast, or wetland area[28,29], co-locating sensors, or installing sensors near one another, i.e., by installing a new sensor near an existing sensor, can reduce the uncertainty of the inundation in that region, and hence reduce the average uncertainty, i.e., mean percent error over all locations, associated with a specific location l (even though the coverage may not be affected in this scenario).

Critical infrastructure facilities density. We use a metric of the density of critical infrastructure facilities per unit area to capture the proximity of potential new sensors to critical infrastructure. Given the locations of the critical facilities in an area, it is possible to calculate the number of facilities per area for each feasible location. However, this would result in a fixed value for nearby solutions, making it difficult to compare solutions for prioritization purposes. It also neglects to include specific values of distances to critical infrastructure facilities. To avoid this problem, we use a kernel density algorithm to quantify the density of point features by generating a kernel (smoothly curved surface) around each feature. The surface value is highest at the location of the facility and diminishes with distance, reaching zero at a radius r. Specifically, the density value is equal to 1 at the location of the facility, with a continuous quartic decay with distance d away from the facility[30], until it reaches a value of 0 at $d = r$. For each possible sensor location l, the value of the critical infrastructure density is calculated as:

$$I_l = \frac{1}{r^2}\sum_{i=1}^{n}\frac{3}{\pi}\left(1-\left(\frac{d_i}{r}\right)^2\right)^2 \quad (1)$$

where r is the radius where the value of the kernel per point reaches zero, n is the number of facilities within the radius r, and d is the distance between a facility i and the coordinate location of location l. The resulting units of the kernel density are still the number of facilities per square distance. However, using this algorithm makes the result of each location more continuous compared to a simple density algorithm because using kernels includes not only the number of close facilities but also the distance between each one of them. The result is a more continuous distribution of critical infrastructure facilities' density compared to using a simple point density approach.

Flood zone. To assess areas with a higher or lower risk of experiencing flooding in a year, we use flood risk values calculated from FEMA's assigned flood zones, and geographic areas depicting varying levels of flood likelihood and hazard exposure. In the definition of flood zones, a 100-year flood is a flood event having a 1% chance of being equaled or exceeded in any given year. Base flood elevation (BFE) is additional information obtained from performing detailed hydraulic analyses of the area indicating the elevation for which floodwater is anticipated to rise during the 100-year flood. The 500-year flood is a flood event having a 0.2% chance of being equaled or exceeded in any given year. These parameters contribute to the designated flood zone for a particular location. For Chatham County, the following flood zones are defined, ranging from high to moderate to low flood risk:

High flood-risk areas.

- Zone VE: Subject to the 100-year flood. Additionally located in a coastal area subject to additional coastal hazards such as storm-induced waves greater than 3 feet.
- Zone A: Subject to the 100-year flood. No BFE information is available.
- Zone AE: Subject to the 100-year flood. BFE information is available.
- Zone AH: Subject to the 100-year flood, but subject to shallow flooding of 1–3 feet.
- Zone A99: Subject to the 100-year flood, but will be protected by a Federal flood protection system.

Moderate flood risk areas.

- Zone X_500: Lies between the limits of the 100-year and 500-year flood events.

Low flood risk areas:

- Zone X: Lies outside the 500-year floodplain.

For further details on the definitions of flood zones, refer to ref. [31].

Damage assessment priority index. The damage assessment priority index (DAPI) used in this study as a measure of social vulnerability and prioritization has been developed by the Chatham Emergency Management Agency (CEMA) in Chatham County. The DAPI is composed of three main components: socio-economic indicators (SEI), vulnerable residential indicators (VRI), and vulnerable housing unit indicators (VHI). Each component is calculated for an area in Chatham County ranging in size from census blocks to census tracts based on available data. The smallest possible resolution is used as available. The SEI is composed of metrics for households below the poverty level, those homes that receive SNAP assistance, and the unemployed population. The VRI measures the number of households that are renter-occupied and owned with no mortgage. The VHI considers the type of unit in the region, i.e., the number of mobile homes, and small/medium/large multi-unit homes. Each of the areas is ranked based on the SEI, VRI, and VHI, with the lowest ranking number, i.e., a rank of 1, indicating the highest vulnerability, and the highest ranking number indicating the lowest vulnerability. The DAPI is then composed of the sum of the three rankings, and the vulnerability of location l denoted V_l is calculated based on the sum of the rankings of the vulnerability indicators at that location:

$$V_l = \mathrm{DAPI}_l = \mathrm{RANK}_{\mathrm{SEI}_l} + \mathrm{RANK}_{\mathrm{VRI}_l} + \mathrm{RANK}_{\mathrm{VHI}_l} \quad (2)$$

In the calculation of the DAPI, the three sets of indicators—SEI, VRI, and VHI—are equally weighted. These factors can be weighted differently based on decision-maker prioritizations. Additional metrics can also be included or replaced based on the available data, as long as the same factors are used across all locations in the study area. The final range of the DAPI across the locations in Chatham County is from 1009 to 3411, with the lowest values indicating the most vulnerable, and therefore highest priority, locations.

The DAPI has multiple benefits to identify community vulnerability compared to other metrics. For instance, most metrics must standardize the resolution of social vulnerability (e.g., at the census tract level). On the contrary, DAPI is able to provide increased resolution information given data availability in Chatham County. The DAPI calculation process generates social vulnerability data at a higher resolution compared to the conventional Social Vulnerability Index (SoVI)[32–34]. This is shown by the population number per area of an index value—where the lower population per area indicates higher precision information produced by the metric. Specifically for the two metrics DAPI and SoVI, while the mean population per polygon for SoVI in Chatham County is 4062, the one for DAPI is 462, 8.8 times lower, providing more precise information on social vulnerability across the county.

Multi-objective optimization problem formulation. Based on these calculated sensor network parameters at each potential new sensor location l, we formulate a multi-objective optimization function. The result is to find and prioritize a set of solution locations P that improves on outcomes across multiple objectives. Each sensor network parameter is an objective in the function. The goal is to find the prioritized solution set P within the full solution space of possible sensor locations L according to the objective function:

$$\max_{l \in L} C_l, -U_l, I_l, F_l, -V_l \quad (3)$$

where for a potential solution location l, C_l indicates network coverage, U_l network uncertainty, I_l critical infrastructure facilities density, F_l flood zone, and V_l social vulnerability.

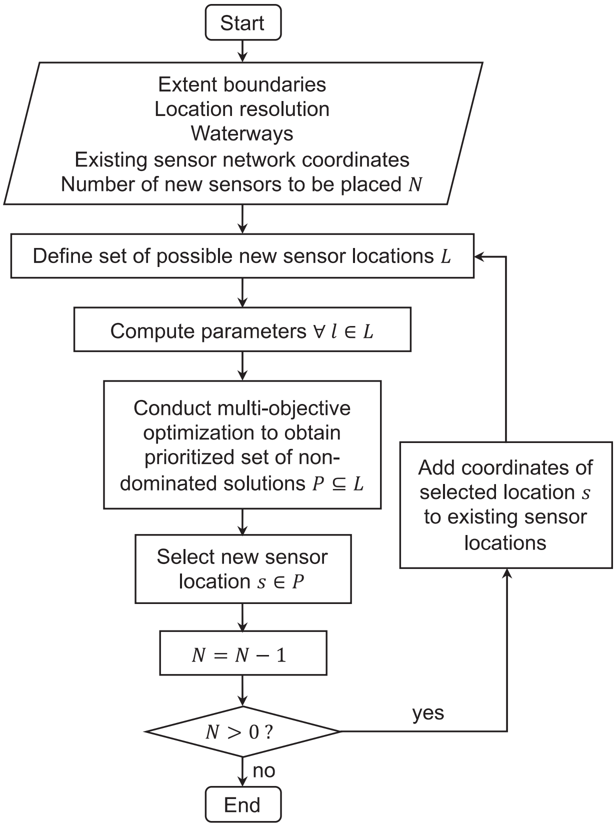

Fig. 6 Flowchart of overall methodology for multi-objective optimization and sensor location selection presented in this study. Inputs, processes, and decision points to select optimal solution locations for a total of N sensors are shown.

Note that this is an unconstrained maximization problem. However, both the uncertainty U_l and the vulnerability V_l need to be minimized given the properties of the parameter. Therefore, a minus sign is included in these two functions. Moreover, there is no need to include constraints in the problem because the model is only going to evaluate solutions from the pre-established set of feasible solution locations L from the full solution space.

To provide communities with decision support rather than having the algorithm directly make the sensor location decisions, we do not weigh the performance metrics in the mathematical model. For instance, for C_l indicating increased network coverage and I_l indicating critical infrastructure facilities density for a potential solution location l, the model should not decide between a location $l_1 = \{C_1 = 1000, I_1 = 5\}$ (i.e., with coverage of 1000 added locations and infrastructure density of 5 facilities per square km) and $l_2 = \{C_2 = 500, I_2 = 10\}$ (i.e., with coverage 500 added locations and infrastructure density 10 facilities per square km). Instead, the model provides both of these as possible solution locations to the decision-maker.

To accomplish this, we use a non-compensatory model that compares each feasible solution and only discards those that are sub-optimal across the optimization function. For example, a potential solution location $l_3 = \{C_3 = 300, I_3 = 3\}$ would be discarded in comparison with the locations l_1 and l_2 because it has lower coverage and infrastructure facilities density than both l_1 and l_2, i.e., it performs worse across both measures. The solution location l_3 has no benefit ahead of l_1 or l_2, and is therefore discarded. The methodology that allows us to discard poor feasible solutions that are implemented in this study is to find the Pareto frontier of the full solution space. To obtain the Pareto frontier, we implement a multi-objective optimization algorithm that finds the set of solutions that are non-dominated[35–37].

The output of the Pareto algorithm is composed of prioritized set of solutions P from the total feasible set of locations L. The size or cardinality of subset $P \subseteq L$ depends on the distribution of values on each sensor network parameter value. For example, in a problem with 20,000 feasible solutions, there can be 1–20,000 solutions in the Pareto set. However, given the nature of the parameters used in this problem, it is expected to find non-dominated Pareto sets composed of <5% of the original set. We have found this to be the case with our demonstration of the approach on the sensor network in Chatham County.

The resulting subset of solution locations P are the prioritized solutions that are optimized across the sensor network parameter values and that are communicated to decision-makers. From these, the final solution location s is selected for the placement of the new sensor. For use of this approach in a sequential expansion of a sensor network, the parameters are then recalculated for the remaining locations, and the multi-objective optimization re-run to obtain a new prioritized set of solution locations P, from which the next final solution location is selected until all sensors are placed.

The full flowchart of the methodology shows both the process of how to select the optimal solution location s in placing an individual new sensor and its use within a larger sequential expansion process (Fig. 6). N denotes the total number of sensors to be placed within the water level sensor network. $N = 1$ for a single sensor placement location decision. Collaborations with community decision-makers throughout the process are essential, particularly in defining the initial extent boundaries and location resolution, and in selecting final sensor locations from the prioritized non-dominated set, i.e., in selecting $s \in P$. The process proceeds until optimized and feasible locations have been selected for all sensors.

Data availability

The water sensor network data for Chatham County, GA, is available at a publicly accessible web portal developed as a collaboration between the research team and the Chatham Emergency Response Agency (CEMA). The portal can be accessed at https://perceptive-bay-214919.appspot.com/?layers=sensors.

Code availability

The code used to analyze and visualize the data used in this study is freely available at the online open repository Zenodo https://doi.org/10.5281/zenodo.7637394. Researchers and community members are encouraged to access this information and to contact the corresponding author as needed regarding the applicability of the work to new study areas and coastal community locations.

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Author contributions

Conceptualization, I.T., J.L., and A.C.; methodology, I.T., J.L., and A.C.; data collection, J.L. and A.C.; analysis of data and results, I.T., J.L., and A.C.; manuscript preparation and revision, I.T., J.L., and A.C.; funding support, I.T.

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The authors declare no competing interests.

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